COVID-19 Classification from Chest X-Ray Images using Convolutional Neural Network (CNN)

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***Abstract* — The COVID-19 pandemic has had a devastating impact on Indonesia and the world at large. As a result, accurate and reliable methods for detecting infected patients are urgently needed. Chest X-Ray Imaging has emerged as a valuable diagnostic tool for detecting COVID-19. In this study, a Convolutional Neural Network (CNN), a type of Deep Learning Model, has been trained to classify Chest X-Ray Images for COVID-19 cases. The proposed CNN model was trained on a dataset of Chest X-Ray images divided into two classes: positive and negative COVID-19 cases. The model achieved an impressive validation accuracy of 97.50% demonstrating its potential to provide valuable information for classifying COVID-19 from Chest X-Ray images. This method shows promise as an effective and easily deployable approach for COVID-19 classification using Chest X-Ray images.**

Keywords — Chest X-Ray Imaging, Classification Convolutional Neural Network, COVID-19, Deep Learning, Pandemic, Patients

I. INTRODUCTION

The COVID-19 pandemic, caused by the SARS-CoV-2 virus, was declared a global pandemic by the WHO in March 2020 **[9]**. The virus is highly contagious and can develop into a potentially fatal acute respiratory distress syndrome, making early detection and diagnosis crucial in controlling its spread **[5]**. Polymerase Chain Reaction (PCR) is currently the widely used standard for confirming COVID-19 disease but is time-consuming and relatively expensive **[1]**. Therefore, many researchers have attempted to automatically diagnose COVID-19 using Chest X-Ray images, which have shown high performance in the classification of lung diseases, and some have achieved high performance using convolutional neural networks **[1]**. However, there is a concern that the neural network might learn features specific to the dataset more than those specific to the disease, and medical research suggests that pneumonia caused by COVID-19 is different from other lung diseases **[1]**. Despite these challenges, accurate diagnostic methods are urgently needed to identify infected patients and control the spread of the virus **[2]**.

The use of Chest X-Ray imaging can be very promising for the assessment of COVID-19 patients, especially in emergencies that require a quick and accurate diagnosis. Deep Learning methods in Artificial Intelligence (AI), particularly Convolutional Neural Networks (CNNs), a high-performance classifier in detecting diseases through Computer Vision **[10]**. This study investigates the CNN model for the classification of COVID-19 using Chest X-Ray images, aiming to provide a more rapid and cost-effective deployment of AI-based tools for detecting COVID-19. Chest X-Ray imaging is essential for excluding other possible lung problems and monitoring the evolution of lung disease **[10]**. Automated systems for detecting and classifying COVID-19 using X-Rays are necessary to save medical professionals time. The study emphasizes the importance of early detection for proper treatment and preventing the disease's spread, as well as the significance of identifying lung involvement for disease management and monitoring.

The proposed study involves using Convolutional Neural Network (CNN) model to classify COVID-19 through Chest X-Ray imaging. The first step is to collect a dataset of labeled Chest X-Ray images, followed by pre-processing the data and training the CNN model on the processed data. The model will then be validated using a test set. The potential application of this study is to provide accurate diagnostic methods for medical practitioners to detect the COVID-19 virus in real-world settings.

II. DATASET

The dataset that will be used in this study was acquired through two sources. The first source is from Wahyono's UGM Google Drive dataset, which contains 156 Chest X-Ray Images that are divided into 2 classes Positive and Negative. The second source is from the Kaggle dataset that is originally used for research purposes through the COVID-19 Image Data Collection repository by Cohen, J.P., Morrison, P., and Dao, L. It contains 454 Chest X-Ray images of patients with lung diseases including COVID-19 as well as metadata describing information such as gender, age, and location of the patients **[4]**. Bennett, J.M. transformed the original dataset into a labeled version.

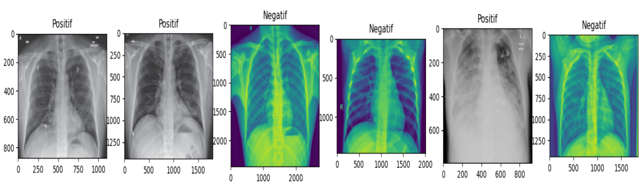

Fig. 1. Samples of Positive and Negative Classes

From the samples in **Fig. 1.**, it is evident that some of the data are yet to be processed and the resolution sizes of the data differ. The negative cases are presented in color, while the positive cases are shown in black and white format. The data distribution of Kaggle's dataset has a balance of labeled data between the training and test validation sets, with 74 images for each positive and negative case in the training data and 20 images in the testing data. On the other hand, the dataset from UGM has an imbalance amount of data for positive and negative cases, with 58 positives and 98 negatives. Therefore, the balanced dataset from Kaggle was chosen to complete the incomplete dataset from UGM. The use of a balanced dataset is crucial to ensure the accuracy and fairness of the model's predictions, as an imbalanced dataset can lead to biased results toward negative cases.

III. Methodology

The methodology employed in this study consists of two main steps: pre-processing and modeling. In the pre-processing step, the dataset was transformed to ensure all images have the same resolution size and normalized to improve the model's performance. The modeling step involves building a Convolutional Neural Network (CNN) architecture with multiple layers, including convolutional, pooling, and fully connected layers, to classify COVID-19 cases from Chest X-Ray images.

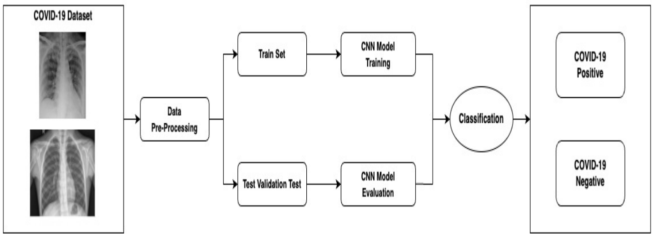

Fig. 2. Methodology Flowchart Diagram

The flowchart in **Fig. 2.** shows the process starting from the COVID-19 data acquisition which undergoes pre-processing before being split into train and test sets. These sets are then used to train and evaluate a CNN model, the trained model is then used for classification, resulting in positive or negative cases of COVID-19.

A. Pre-Processing

The pre-processing methods that are applied to the images include color format conversion, resizing, and normalization. These steps are essential to prepare the data to train the CNN model.

First, the images are converted to the appropriate color format, this method is used to convert the color space of the image from the default BGR format to RGB format. This is important because it ensures that the image has the same color space as the input layer of the CNN model, which is crucial for accurate classification **[9]**.

Next, the images are resized to match the input size required by the CNN model's input layer. This is done to ensure that all images have the same size and dimensions. The input size is specified as the arguments to the function. In this implementation, the images are resized to a specific width and height using the OpenCV library. This step ensures that all images have the same size, which is required for the model to process them consistently, making them easier to process and reducing the amount of memory required to store the images **[2]**.

Finally, the images are normalized. Normalization is the process of scaling pixel values to a standard range, making it easier for the CNN model to learn the features and classify the images accurately, it also improves the convergence **[3]**. The pixel values of the images are divided by 255 to scale them to a range of 0 to 1, making them more manageable for the model to process. Normalizing the images also helps to reduce the impact of lighting and contrast differences, which can improve model performance **[6]**.

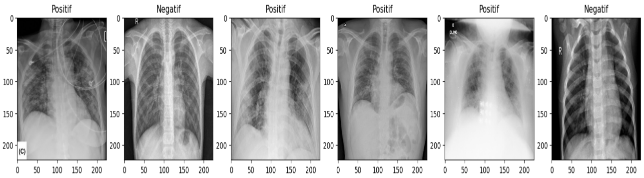

Fig. 3. Samples of Pre-Processed Images

Fig. 3. showcases the result of pre-processed images. The pre-processing step resulted in all data having the same resolution size, which is important for training the model accurately. Previously, the negative cases were presented in color, while the positive cases were shown in black and white format. However, after going through the pre-processing steps, all of the images are now in black and white format, ensuring consistency across the dataset. This standardization in image format is crucial for the model's accuracy. Also, to assign labels to the data, the study used a dictionary to map 'Negative' and 'Positive' to numerical codes 0 and 1 for both the training and testing datasets **[1]**.

B. Modeling

Convolutional Neural Network (CNN) is one of the Deep Learning models that focus on image classification. The CNN neural network is designed to analyze and process images by creating layered structures that represent feature learning. It is an advancement of Multilayer Perceptron and uses neurons with weight, bias, and activation functions **[7]**. CNN uses convolutional layers of neurons arranged to create a filter to get new representative information by moving a certain size convolution kernel over an image **[7]**.

The architecture of CNN is inspired by the human visual cortex to capture spatial and temporal dependencies in an image **[7]**. It combines three architectural ideas to ensure shift and distortion invariance: local receptive fields, shared weights, and spatial or temporal subsampling. The CNN architecture in **Fig. 4.** below, has several layers, including feature extraction with a convolutional layer, followed by a pooling layer, and a softmax classifier. The convolutional layer extracts feature from images, while the pooling layer reduces dimensionality and computation time. After the features are extracted, they are fed into the softmax layer for classification **[5]**.

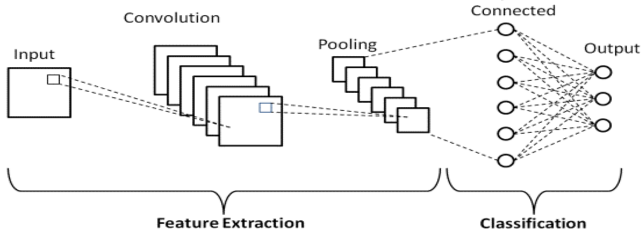

Fig. 4. CNN Architecture

The proposed CNN model will learn the representation of X-Ray images on the Convolution and Pooling layers contained in its architecture and then will perform classification on the fully connected layer to determine whether the X-Ray image given is positive or negative.

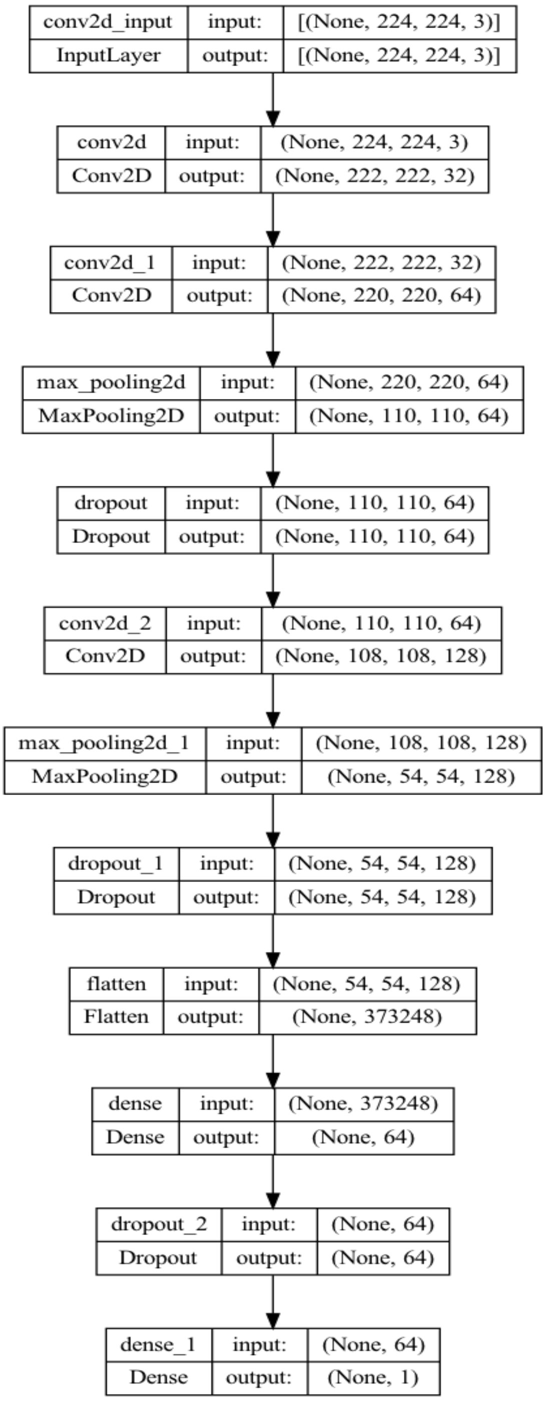

Fig. 5. Model Architecture

Fig. 5. visualized the proposed CNN model's architecture, starting with the Conv2D layer having 32 filters of 3x3 size and ReLU activation function. This layer applies convolutional filters to the input image data, extracting features that are useful for classification. The second Conv2D layer also contains 64 filters with the same activation function and filter size. The output of this layer passes through a MaxPooling2D layer with a pool size of 2x2, decreasing the output's spatial dimensions by a factor of 2.

A Dropout layer then randomly eliminates a fraction of the neurons in the previous layer during training to prevent overfitting. Following that, another Conv2D layer containing 128 filters, a filter size of 3x3, the ReLU activation function, and another MaxPooling2D layer with a pool size of 2x2 is used, further reducing the spatial dimensions.

Another Dropout layer follows, followed by a Flatten layer, which flattens the output of the previous layer into a one-dimensional vector. This flattened output then goes through a Dense layer with 64 neurons and the RelU activation function, followed by another Dropout layer.

Finally, the output passes through a Dense layer having a single neuron and the "sigmoid" activation function, which produces a binary classification output.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 222, 222, 32)      896

 conv2d_1 (Conv2D)           (None, 220, 220, 64)      18496

 max_pooling2d (MaxPooling2D  (None, 110, 110, 64)     0
 )

 dropout (Dropout)           (None, 110, 110, 64)      0

 conv2d_2 (Conv2D)           (None, 108, 108, 128)     73856

 max_pooling2d_1 (MaxPooling  (None, 54, 54, 128)      0
 2D)

 dropout_1 (Dropout)         (None, 54, 54, 128)       0

 flatten (Flatten)           (None, 373248)            0

 dense (Dense)               (None, 64)                23887936

 dropout_2 (Dropout)         (None, 64)                0

 dense_1 (Dense)             (None, 1)                 65

=================================================================
Total params: 23,981,249
Trainable params: 23,981,249
Non-trainable params: 0
```

Fig. 6. Model Summary

The summary of the model as it was shown in **Fig. 6.** above, starts with two convolutional layers, each with 32 and 64 filters respectively, followed by a max pooling layer with a pool size of 2x2 to reduce the spatial dimensions of the output. The first two convolutional layers also include rectified linear unit (ReLU) activation function, which introduces non-linearity into the model **[8]**. A dropout layer is added after the max pooling layer with a rate of 0.25, which helps to prevent overfitting by randomly dropping out some neurons during training.

The next two layers include a convolutional layer with 128 filters and a max pooling layer with a pool size of 2x2, followed by another dropout layer with a rate of 0.25. The output of the last dropout layer is then flattened and passed through two fully connected layers with 64 and 1 neurons respectively. The first fully connected layer has a ReLU activation function and another dropout layer with a rate of 0.5, while the last layer has a sigmoid activation function, which outputs a value between 0 and 1 that represents the probability of the input image belonging to the positive class.

The model is trained for 20 epochs, with a batch size of 32, then the model is compiled with the binary cross-entropy loss function, the Adam optimizer, and accuracy as the evaluation metric. The total number of parameters in the model is approximately 23.9 million, and all the layers are trainable.

IV. Results

This section presents the proposed CNN model's results. Firstly, an overview of the parameters used for validation and evaluation. The accuracy and loss functions for both the train and test samples are plotted for validation, while performance evaluation measures like accuracy, classification report, and confusion matrix are used for evaluation of the testing validation data. These measures offer a detailed assessment of how effective the model is in accurately classifying COVID-19 positive and negative cases.

A. Validation

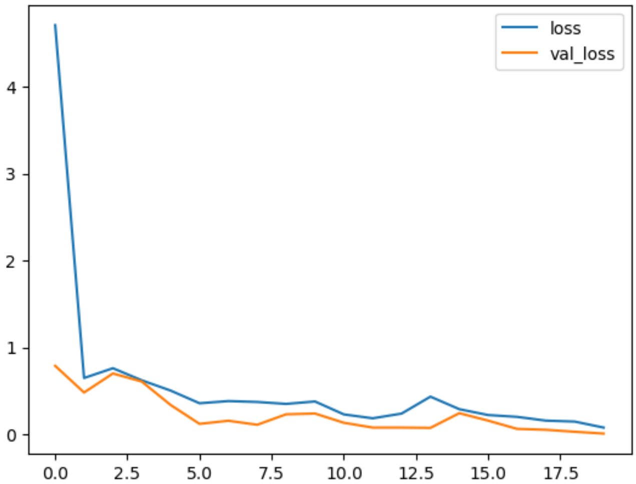

Fig. 7. Model Loss

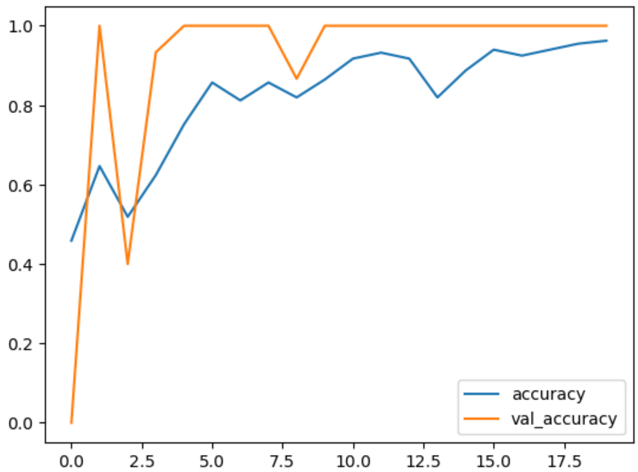

Fig. 8. Model Accuracy

The training and validation loss and accuracy were plotted against the number of epochs (iterations) of the CNN model illustrated in **Fig. 7.** and **Fig. 8.**, then the model was trained for 20 epochs, and the training accuracy increased while the loss decreased with each epoch. The validation accuracy also increased and the validation loss decreased with each epoch, indicating that the model was not overfitting. The final validation accuracy was 1.0, indicating that the model was able to correctly classify all the validation images.

B. Performance Evaluation

TABLE I. Classification Report

Metrics	*Precision*	*Recall*	*F1-Score*
0: Negative	1.00	0.95	0.98
1: Positive	0.95	1.00	0.97
Accuracy	-	-	0.97
Macro Avg	0.97	0.98	0.97
Weighted Avg	0.98	0.97	0.98

The classification report from **Table I.** summarizes the performance of the CNN model when applied to the test validation dataset by showing precision, recall, and F1-score for both positive and negative classes, as well as the overall accuracy. The model achieved high precision and recall for both classes, with an overall accuracy of 0.97. The macro and weighted averages for precision, recall, and F1-score were also high, indicating that the model performed well in both classes and overall.

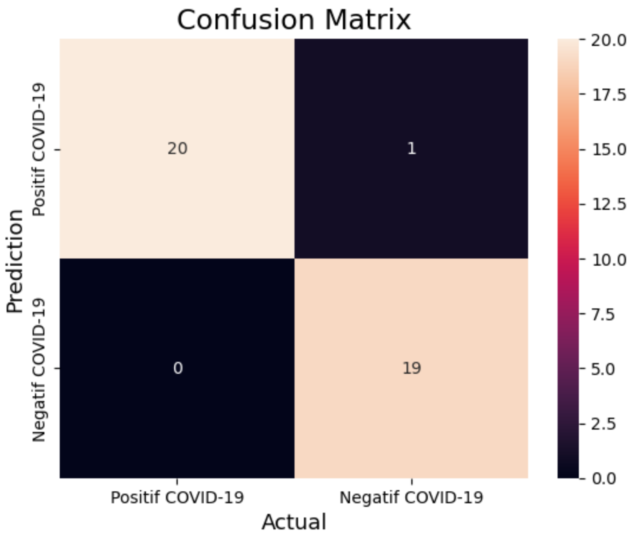

Fig. 9. Confusion Matrix

The confusion matrix from **Fig. 9.** shows that there were 20 true positive predictions (correctly classified Positive samples), 1 false positive prediction (incorrectly classified Negative sample as Positive), 0 false negative predictions (incorrectly classified Positive samples as Negative), and 19 true negative predictions (correctly classified Negative samples). It is reasonable to conclude that the CNN model developed is good enough to classify COVID-19 Chest X-Ray images with high accuracy. This makes it suitable for predicting large numbers of similar data.

V. Conclusions

Based on the results of the proposed model, the CNN model shows high accuracy in classifying COVID-19 Chest X-Ray images. The model is fully automated with an end-to-end structure without the need for manual feature extraction and can be redeveloped when it will retest with another image dataset of a larger size. With 148 images during training, the accuracy was 97.5%. The model evaluation results with test data showed a precision of 98%, recall of 97%, and F1-Score of 98%, the CNN model was considered capable of obtaining accurate results in classifying Chest X-ray images between positive and negative COVID-19 cases, suggesting that it is an effective tool for diagnosis and screening.

However, this study was limited to using 94 positive and 94 negative COVID-19 Chest X-Rays cases due to the use of an open dataset. The limitation was the small amount of COVID-19 X-Ray images, as it was limited to data from 188 patients. To make the model more robust and accurate for medical applications, more images from a source with a larger database should be used, and the model needs to be supported by clinical studies **[7, 8]**.

In future work, the number of data used to train the CNN model can be increased, and the general structure of the convolutional neural network can be restructured to analyze images in more detail. Additionally, a graphical user interface should be developed to enable applications for the use of doctors and radiologists at hospitals and health centers.

Acknowledgment

I would like to express my sincerest gratitude to Mr. Wahyono, S. Kom., Ph.D., for the invaluable guidance and advice provided throughout the Computer Vision and Image Analysis course this semester. Thank you for imparting your extensive knowledge and expertise in the field, which has been instrumental in shaping my ideas and expanding my understanding of the subject matter.

Furthermore, I understand that the study may not have been as comprehensive as some of the other research in the field, which utilizes a larger dataset of images and more advanced neural networks. Nonetheless, I am immensely proud of what I was able to create and the potential practical applications it holds.

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Appendix

Dataset: http://tiny.cc/Dataset-CNN-Rabbani
Source Code: http://tiny.cc/GoogleColab-CNN-Rabbani